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Cities and the Growth of Wages Among Young Workers: Evidence from the NLSY

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Abstract

Human capital-based theories of cities suggest that large, economically diverse urban agglomerations increase worker productivity by increasing the rate at which individuals acquire skills. One largely unexplored implication of this theory is that workers in big cities should see faster growth in their earnings over time than comparable workers in smaller markets. This paper examines this implication using data on a sample of young male workers drawn from the National Longitudinal Survey of Youth 1979 Cohort. The results suggest that earnings growth does tend to be faster in large, economically diverse local labor markets - defined as counties and metropolitan areas - than in smaller, more specialized markets. Yet, when examined in greater detail, I also find that this association tends to be the product of faster wage growth due to job changes rather than faster wage growth experienced while on a particular job. This result is consistent with the idea that cities enhance worker productivity through a job search and matching process and, thus, that an important aspect of 'learning' in cities may involve individuals learning about what they do well.

JEL Classification: J24, R23
Keywords: Agglomeration Economies, Wage Growth, Job Search, Matching

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1 Introduction

Workers in cities tend to earn significantly more than workers situated in smaller labor markets. Glaeser and Mare (2001), for instance, report that average wages in U.S. metropolitan areas are roughly 33 percent higher than those in non-metropolitan areas. Even after controlling for a variety of observable worker-level characteristics, this 'urban wage premium' remains somewhere on the order of 15 to 25 percent.[1]

By and large, this empirical regularity has been interpreted as the reflection of a productivity differential: workers in dense urban agglomerations are simply more productive than their non-urban counterparts. After all, if higher wages did not represent higher productivity, firms would have little incentive to continue to locate in big cities. Yet, as Glaeser and Mare (2001) stress, nearly a quarter of all non-farm establishments in the U.S. are located in the five largest metropolitan areas alone.

Why, then, are workers in cities more productive? Within the last century, a host of theories have weighed in on this matter, suggesting mechanisms that include (*i*) the realization of plant-level economies of scale (Mills (1972), Holmes (1999)), (*ii*) the utilization of greater specialization and trade in production (Abdel-Rahman and Fujita (1990)), (*iii*) faster human capital accumulation (i.e 'learning') due to the spillover of knowledge and greater intensity of interactions (Glaeser (1999)), and (*iv*) the formation of more productive firm-worker matches through a thick-market search externality (Helsley and Strange (1990), Wheeler (2001)).[2] Because all four explanations are consistent with the presence of an urban wage premium, studies correlating urban scale with the *level* of wages offer little insight into

[1]Glaeser and Mare's (2001) estimates do, of course, vary somewhat depending on which data sample they use and how the premium is calculated. Still, many of the estimates which do not control for individual-level fixed effects lie in this range.

[2]As noted in a recent survey by Duranton and Puga (2004), many of these ideas originate with Marshall (1920).

the empirical relevance of each one.

Studies of wage *growth*, by contrast, may provide a better sense of just how important each of these proposed theories really is. In particular, the first two explanations are based on largely static mechanisms: that is, according to these explanations, workers in cities utilize a more efficient production structure than workers in rural areas and so enjoy higher wage levels. Nothing in either one of these theories, however, suggests that wages should grow faster in larger local markets. Hence, when workers move from a small labor market to a large one, they should see the levels of their wages increase as they make the transition from a less-productive technology to a more-productive one. Yet, once they have made this transition, there should be no further effect on earnings.[3]

The latter two explanations, on the other hand, are fundamentally dynamic, suggesting that wages should grow faster over time as workers either accumulate skills at a heightened rate or move into increasingly productive job matches. One way to differentiate between these static and dynamic theories, then, is to examine whether the growth of wages is actually faster within metropolitan areas than it is outside of them. While it would certainly not contradict explanations appealing to scale economies or greater specialization, evidence that wages grow faster in urban areas would at least suggest that some type of learning or matching mechanism is at play.[4]

Moreover, examining the nature of wage growth in local markets of varying sizes may provide a better idea about which of these two dynamic mechanisms may be more relevant in explaining the urban productivity effect. In particular, theories based on learning (or general skill acquisition) suggest that workers in large labor markets should experience faster wage growth on any job they hold. After all, if exposure to diverse urban environments

[3]To be sure, these two explanations can be made dynamic so that productivity also grows faster in large markets. This has *not*, however, been the approach taken in most theoretical formalizations of these ideas.

[4]Indeed, Glaeser and Mare (2001), report evidence from a sample of rural-to-urban migrants that part of the urban wage premium appears to be associated with a level (i.e. static) effect.

increases the rate at which workers accumulate human capital, this process should manifest itself, at least in part, through faster wage growth on each job held.

Theories of firm-worker matching, on the other hand, suggest that wage growth should be strongly tied to a worker's movement from one job to another. Although finding a productive firm-worker match need not involve changing employers, a fair amount of empirical evidence indicates that the process of establishing a productive match tends to involve job changes, especially among young workers. Topel and Ward (1992), most notably, find that the period of time in which workers typically see their wages grow the most (i.e. the first 10 years of a career) is also a period of frequent job changes.[5]

Exploring whether workers in large local markets see faster wage growth 'within' jobs or 'between' jobs, therefore, may provide some evidence on these two theories. Admittedly, the links between each explanation and the nature of wage growth are somewhat tenuous. Faster on-the-job wage growth in cities, for example, could also be interpreted as an indication of better firm-worker matching if better matches increase worker productivity not simply upon their creation, but over time as well. Similarly, one could argue that larger between-job wage changes in cities may emerge from faster learning if workers continue to learn as they make the transition from one employment position to the next.[6]

Nevertheless, faster within-job wage growth can be viewed as a necessary outcome of any theory which rests upon a learning mechanism. As suggested above, learning implies faster human capital accumulation over time which should boost wage growth on-the-job. Greater between-job wage gains, on the other hand, can be viewed as a direct implication of a matching-based explanation for agglomeration economies. Again, in light of Topel and

[5]Specifically, they note that, in a typical 40 year career, male workers change jobs 10 times and see their real wages double. Roughly two-thirds of these job changes and wage growth occur in the first 10 years.

[6]That is, theories of learning suggest that human capital accumulation takes place continuously. Hence, a worker will possess more human capital at the beginning of a new job starting at date t than at the end of an old job ending at date $t - k$ for some $k > 0$.

Ward's (1992) evidence on the importance of job changes, workers in cities should experience larger wage gains through job-to-job transitions if local market scale facilitates the matching process. One can, therefore, interpret any evidence of faster within-job (between-job) wage growth in large urban labor markets as support for a theory of learning (matching). At the same time, any evidence which suggests that within-job (between-job) wage growth is *not* faster in cities will cast some doubt on a learning (matching) explanation.

This paper utilizes data on a sample of young male workers drawn from the National Longitudinal Survey of Youth 1979 Cohort (NLSY79) to examine the relationship between wage growth and the scale of a worker's local market. The results indicate that, on average, wage growth does tend to be positively associated with three measures of local market size: resident population, population density, and extent of industrial diversity. Although the results vary somewhat depending on the sample under consideration, the magnitudes suggest that, conditional on education and experience, a worker in a market with a (log) population 1 standard deviation above the mean (roughly 634,000 residents) may see his wages grow at an average annual rate 0.8 percentage points higher than that of a worker in a market 1 standard deviation below the mean (approximately 23,000 residents).

When overall wage growth is decomposed into within- and between-job components, the evidence suggests that this positive association is driven primarily by job changes rather than growth experienced on-the-job. Conditional on a variety of personal characteristics, including education, experience, industry, and occupation, wage growth associated with job changes is significantly higher in large local markets than in small ones. The wage growth that workers experience while holding individual jobs, on the other hand, shows little association with market size. Following the logic sketched above, these results support the notion that matching, rather than general human capital accumulation, underlies the urban wage premium.

The remainder of the paper proceeds as follows. The next section provides a description of the data and the construction of the individual-level job histories on which the wage analysis is based. Section 3 presents the results looking at overall wage growth. Section 4 then reports the findings for within- and between-job growth. The final section offers some concluding comments.

2 Data

The data used in this paper come primarily from the geocoded version of the National Longitudinal Survey of Youth 1979 Cohort (NLSY79) which provides a weekly labor force history for a sample of more than 12000 men and women who were between the ages of 14 and 21 as of December 31, 1978. In particular, the Work History files of the NLSY79 report for each week beginning in January of 1978, whether an individual worked or not, and if so, which job was held. Because the Work History files allow workers to report up to five jobs held in a given week, some workers are observed in more than one job at a time. Following previous research (e.g. Neal (1999)), I simplify the construction of a time series of jobs held by assuming that a worker's job in a particular week is given by the one at which he worked the most hours.

From these raw data, I limit the sample to the 3003 male respondents from the cross sectional part of the survey. Doing so allows me to avoid issues related to labor force participation which likely influence the composition of the female sample. I further limit the observations to workers for whom I observe a transition from school to full-time work so that I am able to account explicitly for the number of jobs a worker has held in the analysis. A worker's first observed job or job change, for example, may involve a very different pattern of wage growth than his third or fourth job or job change. Including workers who are already observed in the labor force during the first week of 1978 does not permit for this type of analysis because these workers have a labor force history that is partially unobserved.

Jobs are limited to full-time positions - defined as those involving at least 30 hours per week - for which information about industry and occupation could be identified. I only include jobs held after a worker has completed what he reports as his highest level of school attainment throughout the entire survey. I then supplement these work histories with information in the NLSY79 main files concerning a worker's education, race, marital status, and state- and county-of-residence. The final sample includes 1273 male workers who held a total of 5201 jobs between 1978 and 1994.[7] Further information about the construction of the data set appears in the Appendix.

A worker's local labor market is assumed to be given by his metropolitan area- or county-of-residence depending on whether he lives in a metropolitan area or not.[8] In the sample of 1273 workers, a total of 386 local markets are represented at some point. Of these, 204 are metropolitan areas. The remaining 182 are non-metropolitan counties.

Characteristics describing these local markets are derived from three sources: the Census Bureau's Population Estimates Program[9], the USA Counties 1998 on CD-ROM (U.S. Bureau of the Census (1999)) and County Business Patterns (CBP) files for the years 1978 to 1994. The first data set reports estimates of total resident population for each county in the U.S. for each year between 1978 and 1994. The second has information on county-level land

[7] I restrict the analysis to the years 1978-1994 because the NLSY79 conducted interviews on an annual basis over this time frame. Interviews after 1994 were conducted on an every-other-year basis beginning in 1996. Since matching characteristics (e.g. marital status, county-of-residence) which are identified only at the time of interview to a weekly work history likely involves some error (e.g. if a worker reports being single during the interview week of 1992 but married during the interview week of 1993, I assume he is single over the intervening time period), limiting the time between interviews should at least minimize this error.

[8] Metropolitan areas refer either to metropolitan statistical areas (MSAs) or primary metropolitan statistical areas (PMSAs), both of which are constructed as groups of counties. Geographic definitions from the year 1995 are used throughout the analysis. For expositional purposes, the term "city" is sometimes used in place of "metropolitan area."

[9] These data are available at http://www.census.gov/popest/estimates.php.

area which allows me to compile a time series of population densities for all markets.[10] The CBP files contain data on total employment in each county for industries at the four-digit (SIC) level which are used to construct a measure of industrial heterogeneity. Summary statistics describing the worker and local market characteristics used in the analysis below appear in Table 1.

3 Results: Overall Wage Growth

3.1 Main Findings

The data just outlined provide a weekly time series of wages held by a sample of workers on potentially more than one job. To represent these data formally, let workers be indexed by $i = 1, 2, \ldots, N$, and the jobs held by worker i be indexed by $j = 1, 2, \ldots, J_i$ where a particular job j runs from initial week $t^i_{j,start}$ to final week $t^i_{j,end}$. Denoting the logarithms of worker i's initial and final wages on job j as, respectively, $w^i_{j,start}$ and $w^i_{j,end}$, a worker's overall wage growth, G^i, then follows as

$$G^i = \frac{1}{t^i_{J_i,end} - t^i_{1,start}} \left(w^i_{J_i,end} - w^i_{1,start} \right) \tag{1}$$

That is, overall (average) wage growth can be calculated as the difference between this worker's first and last observed log wages, normalized by the total number of weeks that have transpired between the dates on which these wages are observed. For the sake of interpretation, I convert these weekly growth rates into annual rates by multiplying (1) by 52. From Table 1, workers in the sample average nearly 5 percent annual growth in their hourly earnings over time.

[10] I assume a county's land area is given by its 1990 value.

To determine whether wage growth is faster in larger markets, I consider the following regression:

$$G^i = \alpha + \beta' \mathbf{X}^i + \gamma z^i + \epsilon^i \tag{2}$$

where α is a constant; $\mathbf{X}^i$ is a vector of characteristics for worker i, including three educational attainment indicators (bachelor's degree or higher, some college or an associate's degree, high school diploma only), race, marital status, and a quadratic in cumulative weeks of work experience; z^i is a measure of worker i's local market size; and ϵ^i is a stochastic term assumed to be uncorrelated across individuals i.

A local market's scale, z, can be measured in a variety of ways. In an effort to keep the analysis reasonably broad, I look at three quantities commonly used in the literature on urban agglomeration: the logarithm of total resident population, the logarithm of population density, and an index of industrial diversity. Population, of course, provides a sense of how much overall economic activity is present within a worker's broad geographic area, whereas population density (arguably) provides a better measure of how much of that activity a worker sees on average.[11] Diversity, by contrast, directly measures how many different industries are present in the local market and, thus, may represent the number of distinct 'experiences' an individual has.[12] Formally, I measure industrial diversity by the 'Dixit-Stiglitz' index of Ades and Glaeser (1999) given by

$$\text{Diversity} = \left(\sum_k \left(\frac{\text{Emp}_k}{\text{Emp}} \right)^{\frac{1}{2}} \right)^2$$

[11] Ciccone and Hall (1996) argue that density, not overall size, enhances productivity. Similarly, Glaeser (1999) models learning as a function of density rather than raw population.

[12] This feature may, therefore, influence both the extent to which individuals learn (e.g. observing different types of work as in Jacobs (1969)) as well as the degree to which workers can find productive matches (i.e. by providing different work options).

where Emp_k is the total employment in (4-digit SIC) industry k in the local market, and Emp represents total employment. By construction, larger values of this index represent greater diversity.

Estimation of (2), unfortunately, is not completely straightforward since a number of the regressors tend to change in the time over which G^i is measured. Specifically, although education and race are constant throughout a worker's observed job history in these data[13], experience, marital status, and the scale of the local market, z^i, all tend to change. I, therefore, have to select particular values for these covariates in order to estimate (2). For cumulative work experience and marital status, I select the values observed at the end of a worker's job history. For local market scale, z^i, I choose the average value over the observed jobs comprising the history.[14]

The resulting coefficient estimates appear in Table 2. For the most part, they are quite intuitive. Workers with higher levels of education, for example, see significantly higher average rates of overall wage growth than workers with lower levels of education. Similarly, wage growth tends to be faster among whites and those who are married. Experience and its square do not produce significant coefficients, but the point estimates suggest a wage growth pattern that is consistent with a standard hump-shaped age-earnings profile.

The results also reveal a positive association between overall average wage growth and each of the three measures of local market scale considered. Moreover, the estimated population, density, and diversity coefficients are all statistically significant at conventional levels (i.e. at least 10 percent). They suggest that a 1 standard deviation increase in a local labor market's population, density, or diversity is accompanied by a 0.4 percentage point rise in a worker's average hourly earnings growth (at an annual rate). So, the implied difference

[13]Recall, the sample is limited to jobs held after a worker has completed all schooling reported in the survey.

[14]That is, I use the average log population, log density, or diversity across the markets in which this worker was observed between 1978 and 1994.

between overall average wage growth in Cheyenne, Wyoming - with a population of 78000, a density of 29 residents per square mile, and a diversity index of 109 in the year 1994 - and Chicago, Illinois - with a population of more than 7.7 million, a density of 4100 residents per square mile, and a diversity index equal to 354 (also in 1994) - lies between 1 and 1.3 percentage points per year. Given a mean of 4.9 percent average annual wage growth in the sample, this implied difference is quite sizable.

3.2 Robustness: Non-Movers

As noted above, the estimation of (2) is somewhat problematic in that some of the covariates change over the course of a worker's observed job history, including his local market of residence. Using the average population, density, and degree of industrial heterogeneity taken across all of the markets in which a worker has been employed, therefore, likely introduces some measurement error which may complicate the interpretation of the results. For example, some workers may start their careers in small markets where they experience slow wage growth, but then move to a large city where their wages grow much faster. Simply using the average size of the markets in which these movers lived is clearly an imperfect way to correlate overall wage growth with market scale in these instances.[15]

One (still imperfect) way to address this particular matter is to confine the sample of workers to those who do not move or, at least, those who only report a single market throughout the entire series of interviews. This procedure more closely ties a worker to a single market so that the estimated association between wage growth and the average characteristics of a worker's labor market can be drawn more clearly. In particular, it

[15] Of course, if wage growth wage is directly (or even inversely) tied to local market scale, estimating (2) using average market size should still pick up this relationship. A worker who spends more time in a large city than another worker, under this scenario, will have both faster wage growth and a larger value for average local market size.

eliminates the possibility that some of a worker's overall wage growth is driven by shifts in the level of his wages when he moves from a small market to a large one (or vice versa). Recall from the Introduction, the basic intent behind looking at wage *growth* is to distinguish between static and dynamic theories of agglomeration economies. Confining the sample to non-movers may help to accomplish this task more effectively.

Of the 1273 workers in the full sample, 414 report full-time jobs in more than one local market, leaving a sample of non-movers with 859 observations. The results from this particular subset of the sample suggest considerably smaller scale effects on overall wage growth. With each independent variable, the coefficient estimate (standard error) drops substantially: 0.0012 (0.0015) for log population as opposed to 0.0023 previously; 0.0013 (0.0016) for log density instead of 0.0027; 0.016 (0.03) for diversity rather than 0.043. What is more, none of these associations are significant in a statistical sense which, unfortunately, tempers the conclusion drawn above. Collectively, then, the results suggest that, while overall wage growth may be somewhat faster in large markets, the evidence is not overwhelming. A closer look at this particular result is considered in the next section.

4 Results: Within- and Between-Job Growth

4.1 Decomposing Overall Growth

Given an entire history of wages for a set of jobs that a worker holds, overall wage growth can be decomposed into the sum of two parts: one associated with the growth of wages on (or within) particular jobs, and the other due to job changes. Using the notation from above, the data reveal a set of initial and final (log) wages $\{w^i_{j,start}, w^i_{j,end}\}$ as well as starting and stopping times $\{t^i_{j,start}, t^i_{j,end}\}$ for jobs $j = 1, 2, \cdots, J_i$ for each worker i. This allows me to express overall wage growth, G^i, given by (1) as the following sum of the differences between initial and final wages:

$$G^i = \frac{1}{t^i_{J_i,end} - t^i_{1,start}} \Big((w^i_{J_i,end} - w^i_{J_i,start}) + (w^i_{J_i,start} - w^i_{J_i-1,end}) + (w^i_{J_i-1,end} - w^i_{J_i-1,start})$$
$$+ \cdots + (w^i_{2,end} - w^i_{2,start}) + (w^i_{2,start} - w^i_{1,end}) + (w^i_{1,end} - w^i_{1,start}) \Big) \quad (3)$$

Collecting the 'within-job' growth terms, $(w^i_{j,end} - w^i_{j,start})$, and the 'between-job' growth terms, $(w^i_{j,start} - w^i_{j-1,end})$, G^i has the following straightforward decomposition

$$\begin{aligned} G^i &= \sum_{j=1}^{J_i} \frac{w^i_{j,end} - w^i_{j,start}}{t^i_{J_i,end} - t^i_{1,start}} + \sum_{j=2}^{J_i} \frac{w^i_{j,start} - w^i_{j-1,end}}{t^i_{J_i,end} - t^i_{1,start}} \\ &\equiv WG^i + BG^i \end{aligned} \quad (4)$$

Table 1 reports a few summary statistics for these two components. On average, the wage growth that workers experience within the jobs they hold (WG^i) amounts to roughly 2.6 percent per year, while that due to job changes (BG^i) is approximately 1.9 percent per year. These figures suggest that, although within-job wage growth contributes more to overall wage growth than between-job growth, the movement from one job to another clearly plays a significant role in the growth of earnings over time.

To determine whether the positive associations between overall average wage growth and local market scale documented in the previous section stems from the growth of wages within jobs or between jobs (or possibly both), I estimate regressions analogous to equation (2) where WG^i and BG^i replace overall growth G^i as the dependent variable.[16] The estimates appear in Table 3. In general, they do show some evidence that larger, denser, more diverse

[16] As with overall growth, these terms have been multiplied by 52 to convert weekly growth rates to annual rates.

local markets tend to be characterized by faster within- and between-job wage growth.[17] All of the coefficients on population, density, and the diversity index are positive, although only the density coefficient in the between-job wage growth specification differs statistically from zero.

In addition, between the two sets of results, the estimated associations between the three market size variables and wage growth are somewhat larger in the between-job regressions. Looking at the within-job regressions, for example, the point estimates suggest that a 1 standard deviation increase in log population, log density, or the index of industrial diversity tend to be accompanied by a 0.2 to 0.26 percentage point increase in annual rate of within-job wage growth. These same increases in market size correlate with a 0.3 to 0.6 percentage point increase in the annual rate of between-job growth. In general, then, these results provide some evidence that large local markets exhibit greater wage growth through job changes than small markets. There is less evidence that the same holds for within-job growth.

A similar conclusion emerges when the sample is confined to non-movers only.[18] Looking at within-job growth, WG^i, as the dependent variable, the resulting coefficients drop substantially, much as the overall wage growth coefficients did. The estimates (standard errors) for log population, log density, and diversity in this case are -0.0001 (0.001), 0.0003 (0.0015), and -0.009 (0.03) rather than 0.0016, 0.0013, and 0.0027 for the full sample. With between-job growth, BG^i, as the dependent variable, however, the estimates tend to be remarkably similar across full and non-mover samples. The coefficients (standard errors)

[17] Note, only a subset of the 1273 workers in the sample are observed in more than one full-time job. Because I treat all workers who hold only one job as missing in the between-job growth regressions (rather than setting BG^i equal to zero), the number of observations used to estimate the between-job growth regressions is 989.

[18] There are, again, 859 non-movers in the sample. Of these, 589 experience at least one job change and so appear in the between-job growth regressions.

on log population, log density, and diversity are 0.003 (0.002), 0.0033 (0.002), and 0.053 (0.035) as opposed to 0.0018, 0.004, and 0.036.[19]

Evidently, the drop off in the coefficient estimates noted in Section 3.2 when overall growth was regressed on market size using the sample of non-movers appears to be driven by the decrease in the within-job component, not the between-job part. I interpret this particular finding as further evidence of a tenuous relationship between within-job wage growth and market size. At the same time, however, between-job wage growth's association with market size seems comparatively more important and robust. Hence, to the extent that overall average wage growth is higher in larger local markets, it seems to be the product of wage gains garnered through job changes.

Still, given the changing nature of many of the covariates used in these regressions, as well as the fact that workers tend to hold different types of jobs during their careers (i.e. workers frequently change industries and occupations), looking at total within- and between-job wage growth may not completely capture their associations with local market scale. At this point, therefore, I turn to the analysis of wage growth associated with individual jobs and job changes.

4.2 Individual Within-Job Observations

The job history data in the NLSY79 identify a series of jobs $j = 1, 2, \cdots, J_i$ across a sample of workers, $i = 1, 2, \cdots, N$, from which it is straightforward to construct a set of within-job wage growth rates $\{wg_j^i\}_{j=1}^{J_i}$ where

$$wg_j^i = \frac{1}{t_{j,end}^i - t_{j,start}^i} \left(w_{j,end}^i - w_{j,start}^i \right) \tag{5}$$

[19] Although still insignificant at conventional levels, the p-values for these three coefficients estimated using the non-mover sample (with respect to a null that each is 0) are reasonably small: 0.127, 0.11, and 0.136 for, respectively, log population, log density, and diversity.

That is, I define wage growth on a particular job j for worker i as the difference between the log final wage and the log initial wage, normalized by the number of weeks the job was held.[20] These growth rates are then used to estimate

$$wg_j^i = \alpha + \beta' \mathbf{X}_j^i + \theta' \mathbf{M}_j + \gamma z_j^i + \epsilon_j^i \tag{6}$$

where $\mathbf{X}_j^i$ and z_j^i denote a worker's personal characteristics and a measure of his local market's size as before. Now, however, these covariates are linked to particular jobs, j, where the values of $\mathbf{X}_j^i$ and z_j^i are set equal to their values at the end of the job, $t_{j,end}^i$.[21] In addition, I have included a vector, $\mathbf{M}_j$, of 8 occupation and 12 industry indicators describing job j in an effort to further control for exogenous differences in the rate of wage growth across types of work.[22] Although estimation of (6) proceeds as above by ordinary least squares, I now adjust the standard errors for both heteroskedasticity and potential correlation within individuals, i, of the stochastic terms ϵ_j^i.

Estimates appear in Table 4A. Just for the sake of comparison, I have reported two specifications for each size variable: one in which the vector of occupation and industry dummies is included and one in which it is not (as in the estimation presented thus far). In either case, the resulting coefficients on log population, log density, and the diversity

[20] As with overall wage growth, I convert these weekly growth rates into annual terms by multiplying wg_j^i by 52.

[21] Results were very similar using the values of $\mathbf{X}_j^i$ and z_j^i from the beginning of the job.

[22] Occupations include (1) Professional and Technical; (2) Managers, Officials, and Proprietors; (3) Sales; (4) Clerical and Kindred; (5) Craft, Foremen, and Kindred; (6) Operatives; (7) Non-farm Laborers; (8) Service. Industries include (1) Agriculture, Forestry, Fisheries; (2) Mining; (3) Construction; (4) Durable Manufacturing; (5) Non-durable Manufacturing; (6) Transportation, Communications, Utilities; (7) Wholesale Trade; (8) Retail Trade; (9) FIRE; (10) Business and Repair Services; (11) Personal, Entertainment, and Recreation Services; (12) Professional and Related Services.

index are positive, yet statistically insignificant. Such findings suggest that, on average, city dwellers do not seem to experience faster wage growth on jobs than workers in smaller labor markets.

The growth rates calculated as in (5), unfortunately, have the property that they are, on average, negative in the sample (see Table 1). This result emerges in spite of the fact that the total within-job wage growth experienced by workers in this sample, WG^i, is, on average, positive (again, see Table 1). This feature of the data likely results from the presence of jobs with extremely short durations over which wages decline. These within-job observations produce extremely large, negative growth rates when converted into annual terms which are then given the same weight in the estimation as longer-lasting jobs which carry small, but positive growth rates. The within-job wage changes a worker experiences, therefore, may very well sum to a positive number over all of the jobs he holds in his career, but the average *rate* of within-job wage growth may be negative.

To avoid this peculiarity in the data, I repeat the analysis using within-job wage *changes* which I compute as the difference between the log final wage on a job and the log initial wage. Those results appear in Table 4B. While a number of the personal characteristics produce significant coefficients in this case - notably education and marital status which generate positive associations - the three measures of local market scale remain insignificant. There is, then, little evidence that either raw wage changes or rates of wage growth experienced within jobs differ significantly across local markets of varying sizes.

4.3 Individual Between-Job Observations

The wage growth that a worker experiences through a job change can be calculated as follows

$$bg_j^i = \frac{1}{t_{j,start}^i - t_{j-1,end}^i}\left(w_{j,start}^i - w_{j-1,end}^i\right) \tag{7}$$

That is, the rate of wage growth associated with moving into a job j is simply the difference between that job's (log) starting wage and the (log) final wage of the job that preceded it, $j-1$. I then normalize this difference by the length of time between the two jobs and rescale by 52 to obtain an annual rate. Following the within-job analysis from the last section, I estimate the association between bg_j^i and local market scale in a manner analogous to within-job growth:

$$bg_j^i = \alpha + \beta' \mathbf{X}_j^i + \theta' \mathbf{M}_j + \gamma z_j^i + \epsilon_j^i \tag{8}$$

All of the terms in (8) are the same as in equation (6). In this case, however, the individual and market size characteristics, $\mathbf{X}_j^i$ and z_j^i, are evaluated at the beginning of the new job j.[23]

Results appear in Table 5A. Notably, each of the three measures of local market size produces a positive and statistically significant coefficient, regardless of whether I control for industry and occupation effects or not. What is more, the magnitudes are large in an economic sense. A 1 standard deviation increase in log population, log density, or diversity for instance correlates with a 40 log point increase, approximately, in the rate of between-job wage growth. Although this figure may seem implausible, it should be noted that the mean between-job growth rate in these data (expressed at an annual rate) is 245 log points.[24]

[23] As suggested by the notation, the vector of occupation and industry indicators, $\mathbf{M}_j$, refers to the job to which a worker is moving (j) rather than the job from which he moves ($j-1$). In the next section, I consider a specification which also controls for whether a given job change entails a change of industry.

[24] This comes as a consequence of extrapolating wage changes associated with moving from one job to another into an annual growth rate. A 10 log point (i.e. approximate percentage point) increase in a worker's wages associated with moving from one job in week t to another job in week $t+1$, therefore, will generate a 520 log point wage growth rate.

The 40 log point association, therefore, is only about 16 percent of the mean which is still large, but not unreasonably so.

One unfortunate property of the between-job growth measure given by (7), however, is its dependence on the time that transpires between the end of one job and the start of the next. This dependence, for example, gives a 10 log point increase in wages between a pair of jobs separated by 2 weeks only half the weight that an identical 10 log point increase between a pair of jobs separated by a single week.[25] Arguably, these job changes should be treated identically in the analysis. To eliminate this feature of the wage growth measure, I also consider between-job wage changes, just as I did in the within-job analysis, as the dependent variable in equation (8).

Those estimates are reported in Table 5B. In terms of statistical importance, the same basic conclusions can be drawn regarding the association with local market scale. Job changes occurring in large, diverse markets tend to be associated with greater changes in log wages than job changes which occur in small, specialized markets. Indeed, the coefficients on the three scale variables are, in all but one instance, positive and statistically non-zero. They also imply relatively large associations. The point estimates indicate that a 1 standard deviation increase in any of the scale variables tends to be associated with a 1 percentage point increase, roughly, in the average wage change associated with moving from one job to another. As with the results on between-job wage growth, this association is on the order of 16 percent of the mean log wage change in the sample.

4.4 Robustness

This section considers a number of alterations to the analysis in an effort to assess the robustness of these findings.[26] First, given that I am examining the first several jobs that

[25]That is, the former produces a value of bg_j^i equal to 260 whereas the latter yields a value of 520.

[26]I also estimated equations (6) and (8) with individual-specific fixed effects. Unfortunately, sweeping out individual means eliminates much of the variation in these data. None of the resulting population, density,

workers hold, it is possible that the rate of wage growth experienced either within a particular job or between a given pair of jobs may depend on how many jobs a worker has held. First jobs, for instance, may involve particularly slow rates of wage growth because many of them may be entry-level positions with little room for advancement. Similarly, there may be an especially large average wage change involved with the first few job changes a worker makes because changes made early in one's career may represent the movement into increasingly productive job matches. The first robustness check adds a set of five 'episode' indicators (first, second, third, fourth, fifth or higher job or job change) to equations (6) and (8).[27]

The second modification returns to the exercise performed above in which the samples of individual within- and between-job experiences are limited to workers who are only observed in a single market during the entire survey. Again, looking at non-movers provides a stronger link between the observed characteristics of a worker's local market and his rate of wage growth. Otherwise, a worker may spend time in large city, say, where he experiences rapid learning or finds a productive line of work and then moves on to a smaller market. The fact that this worker spent time in a large urban environment may influence his wage growth, either between or within jobs, in the smaller market.

Moves may also account for much of the between-job results shown in Tables 5A and 5B. In particular, if workers receive a boost in their wage earnings upon moving from a small market to a large one (say, due to one of the static theories of agglomeration economies described in the Introduction), we should observe a positive association linking between-job changes and local market size. Recall, the size of a local market associated with a between-

or diversity coefficients were significant, although all were positive (and roughly similar to those already presented) in the between-job regressions, but negative in the within-job regressions.

[27] I also tried interacting these episode indicators with log population, log density, and diversity to capture any differences in the local market scale 'effects' by job and job-change number. Wald tests, however, failed to reject the null hypothesis that all of these coefficients were identical.

job change in this analysis is given by the population, density, or diversity of the market in which the *new* job is located. Looking only at non-movers eliminates this possibility.

The third and fourth robustness checks only involve job changes. Previous work (e.g. Jacobson et al. (1993)) indicates that job changes involving changes of industry (or, at least, changes in the types of tasks performed) rather than merely changes of employer tend to be accompanied by relatively low between-job wage growth. This result is commonly interpreted in terms of the loss of sector-specific human capital when a worker switches from one industry to another. Because I am looking at early job experiences, however, industry changes might also represent a worker's movement from a line of work in which he is poorly matched to one in which he is more productively matched. To account for any possible influence of industry changes on between-job wage growth, I include in equation (8) a dummy variable representing whether a job change also involves a change of industry.

The final modification considers an alternative means to approach geographic moves. In particular, while confining the sample to non-movers should eliminate the effects of residence changes on between-job wage growth, doing so involves dropping nearly a third of the sample.[28] To preserve all of the observations, I consider a strategy in which the effects of geographic moves are represented by a set of four indicators added to equation (8) which reflect whether a job change also involves an urban-to-urban, rural-to-rural, urban-to-rural, or rural-to-urban change of residence.[29] Categorizing moves by one of these four types is intended to account for differences in the levels of wages between metropolitan and non-metropolitan areas.

The results appear in Table 6. To keep the presentation of the results concise, I have only reported the estimated coefficients on the three scale variables. Most of the remaining

[28] Again, 414 of the 1273 workers in the full sample are observed making a geographic move at some point.

[29] "Urban" refers to residence in a metropolitan area; "rural" refers to residence outside of a metropolitan area.

coefficients do not differ substantially from what is reported above.

Two broad patterns characterize the estimates. First, none of the within-job coefficients differ statistically from zero. Although the wage growth coefficients are positive, the wage *change* coefficients are negative, suggesting that, on the whole, there is little evidence that workers who live in cities experience larger wage gains on-a-job than workers in smaller markets.

Second, however, workers in cities do seem to experience larger wage gains when changing jobs than workers located in smaller areas. The majority of the population, density, and diversity coefficients for both the between-job wage growth and wage change regressions are statistically significant at conventional levels, and their magnitudes are very similar to those reported in Tables 5A and 5B. This is even true when the sample is confined to the 2072 job changes observed among non-movers. As before, these findings suggest that, if workers in cities do experience faster wage growth over time, that growth is more related to job changes than to within job growth.

5 Conclusion

Workers in large urban areas tend to earn more, on average, than similar workers who live in smaller places. This paper has offered evidence that the wages of workers located in large markets also tend to grow faster over time. Although the significance of the estimates vary depending on the particular sample of workers used, this finding is at least qualitatively consistent with learning- and matching-based theories of agglomeration economies which stress dynamic mechanisms that increase a worker's productivity over time.

Upon closer inspection, much of this association seems to be driven by wage growth achieved through job changes rather than from growth on-the-job. Based on a sample of individual jobs and job changes, I find that workers who change jobs in large, diverse local markets tend to see significantly greater wage gains than observationally equivalent workers in small, specialized markets. Yet, workers in large markets do not tend to see greater wage gains experienced on-the-job than workers in small markets. Interpreting faster within-job wage growth as a necessary implication of a learning mechanism and faster between-job wage growth as a necessary implication of a matching mechanism, these findings provide greater support for the latter explanation for agglomeration economies.

To be sure, identifying the means by which workers in dense urban markets come to be more productive than workers located elsewhere is a complicated task, and the evidence reported here only offers a limited set of insights into the issue. Further research on this topic, therefore, is certainly warranted. Indeed, in spite of the general movement among urban economists toward empirical studies of the microfoundations of urbanization and localization economies (see Rosenthal and Strange (2004) for a survey), there remains a surprising lack of research investigating the nature of the labor force activities of workers situated in local markets of varying sizes. Only through research of this sort will it be possible to develop a firm understanding of how spatial agglomeration affects economic outcomes.

Table 1: **Summary Statistics**

Variable	Mean	Standard Deviation	Minimum	Maximum
College	0.36	0.48	0	1
Some College	0.2	0.4	0	1
High School	0.37	0.48	0	1
Cumulative Weeks of Work Experience	478.6	192.8	3	869
Married	0.6	0.49	0	1
Non-White	0.17	0.37	0	1
Overall Wage Growth, G^i	0.049	0.08	-0.65	0.83
Within-Job Growth Component, WG^i	0.026	0.07	-0.49	0.7
Within-Job Wage Growth	-0.02	1.8	-100.8	45.5
Within-Job Wage Changes	0.063	0.33	-2.64	3.98
Between-Job Growth Component, BG^i	0.019	0.09	-1.2	0.76
Between-Job Wage Growth	2.45	16.3	-142.3	140.1
Between-Job Wage Changes	0.06	0.47	-3.1	2.85
Population	466721.9	998962.1	3517	8626114
Population Density	481.7	1628.9	2.57	26367.9
Dixit-Stiglitz Diversity Index	135.9	82.8	12.1	357.2

Note: Personal characteristics calculated using 1273 individual observations. Experience and marital status represent values at the end of each worker's observed job history. Overall wage growth, the within- and between-job components are calculated from 1273 observations. Within-job wage growth and changes are calculated using 5201 jobs; between-job wage growth and changes are calculated using 3923 job changes. Local market characteristics are given by the averages for each of the 386 local markets identified in the sample.

Table 2: Overall Wage Growth

Variable	*I*	*II*	*III*
College	0.027*	0.028*	0.027*
	(0.007)	(0.007)	(0.007)
Some College	0.024*	0.024*	0.024*
	(0.006)	(0.006)	(0.006)
High School	0.012*	0.012*	0.012*
	(0.006)	(0.006)	(0.006)
Experience	0.01	0.01	0.01
	(0.08)	(0.08)	(0.08)
Experience	-0.0002	-0.0002	-0.0002
Squared	(0.0008)	(0.0008)	(0.0008)
Married	0.014*	0.014*	0.014*
	(0.005)	(0.005)	(0.005)
Non-White	-0.017*	-0.017*	-0.016*
	(0.006)	(0.006)	(0.006)
Log Population	0.0023*	–	–
	(0.0013)		
Log Density	–	0.0027*	–
		(0.0014)	
Diversity	–	–	0.043*
			(0.025)
R^2	0.037	0.037	0.037

Note: 1273 observations. Coefficients on experience have been multiplied by 1000, experience squared by 10000, the Dixit-Stiglitz diversity index by 1000. An asterisk (*) denotes significance at 10 percent confidence or better. Heteroskedasticity-consistent standard errors appear in parentheses.

Table 3: Within- and Between-Job Components

	Within Component, WG			*Between Component, BG*		
Variable	*I*	*II*	*III*	*I*	*II*	*III*
College	0.032*	0.032*	0.032*	-0.0006	-0.001	-0.0008
	(0.007)	(0.007)	(0.007)	(0.01)	(0.01)	(0.01)
Some College	0.017*	0.017*	0.017*	0.002	0.003	0.002
	(0.007)	(0.007)	(0.007)	(0.01)	(0.01)	(0.01)
High School	0.009	0.009	0.009	0.001	0.002	0.001
	(0.007)	(0.007)	(0.007)	(0.01)	(0.01)	(0.01)
Experience	-0.02	-0.02	-0.02	-0.1	-0.1	-0.1
	(0.06)	(0.06)	(0.06)	(0.1)	(0.1)	(0.1)
Experience	0.0006	0.0006	0.0006	0.0006	0.0006	0.0005
Squared	(0.0006)	(0.0006)	(0.0006)	(0.001)	(0.001)	(0.001)
Married	0.01*	0.01*	0.01*	0.009	0.01	0.009
	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)
Non-White	-0.004	-0.004	-0.004	-0.02*	-0.02*	-0.02*
	(0.005)	(0.006)	(0.006)	(0.009)	(0.01)	(0.009)
Log Population	0.0016	–	–	0.0018	–	–
	(0.0013)			(0.0017)		
Log Density	–	0.0013	–	–	0.004*	–
		(0.0014)			(0.002)	
Diversity	–	–	0.027	–	–	0.036
			(0.025)			(0.03)
R^2	0.038	0.037	0.037	0.017	0.019	0.017

Note: 1273 within-job and 989 between-job observations. Coefficients on experience have been multiplied by 1000, experience squared by 10000, the Dixit-Stiglitz diversity index by 1000. An asterisk (*) denotes significance at 10 percent confidence or better. Heteroskedasticity-consistent standard errors appear in parentheses.

Table 4A: Within-Job Wage Growth

Variable	*I*	*II*	*I*	*II*	*I*	*II*
College	-0.08	-0.07	-0.09	-0.07	-0.08	-0.07
	(0.11)	(0.09)	(0.11)	(0.1)	(0.1)	(0.1)
Some College	-0.01	-0.02	-0.01	-0.02	-0.01	-0.02
	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)
High School	-0.005	-0.01	-0.004	-0.01	-0.007	-0.01
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Experience	-0.04	-0.08	-0.04	-0.08	-0.04	-0.08
	(0.4)	(0.4)	(0.4)	(0.4)	(0.4)	(0.4)
Experience Squared	0.005 (0.006)	0.005 (0.006)	0.005 (0.006)	0.005 (0.006)	0.005 (0.006)	0.005 (0.006)
Married	-0.05	-0.04	-0.04	-0.04	-0.05	-0.05
	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)
Non-White	-0.01	-0.01	-0.01	-0.02	-0.01	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Log Population	0.017	0.016	–	–	–	–
	(0.02)	(0.024)				
Log Density	–	–	0.024	0.023	–	–
			(0.025)	(0.026)		
Diversity	–	–	–	–	0.29	0.27
					(0.41)	(0.43)
Industry Indicators	No	Yes	No	Yes	No	Yes
Occupation Indicators	No	Yes	No	Yes	No	Yes
R^2	0.002	0.004	0.002	0.005	0.002	0.004

Note: 5201 observations. Coefficients on experience have been multiplied by 1000, experience squared by 10000, the Dixit-Stiglitz diversity index by 1000. Heteroskedasticity-consistent standard errors appear in parentheses.

Table 4B: Within-Job Wage Changes

Variable	I	II	I	II	I	II
College	0.1*	0.082*	0.1*	0.082*	0.1*	0.083*
	(0.016)	(0.019)	(0.016)	(0.019)	(0.016)	(0.019)
Some College	0.037*	0.029*	0.037*	0.029*	0.037*	0.029*
	(0.016)	(0.017)	(0.016)	(0.017)	(0.016)	(0.017)
High School	0.021*	0.019	0.021*	0.019	0.021*	0.018
	(0.012)	(0.013)	(0.012)	(0.013)	(0.012)	(0.013)
Experience	0.04	0.05	0.04	0.05	0.04	0.05
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Experience Squared	0.004*	0.004*	0.004*	0.004*	0.004*	0.004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Married	0.024*	0.026*	0.025*	0.026*	0.024*	0.026*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Non-White	-0.009	-0.01	-0.009	-0.01	-0.008	-0.01
	(0.01)	(0.01)	(0.1)	(0.01)	(0.01)	(0.01)
Log Population	0.0016	0.0001	–	–	–	–
	(0.003)	(0.003)				
Log Density	–	–	0.0016	0.0002	–	–
			(0.003)	(0.002)		
Diversity	–	–	–	–	0.023	-0.009
					(0.054)	(0.05)
Industry Indicators	No	Yes	No	Yes	No	Yes
Occupation Indicators	No	Yes	No	Yes	No	Yes
R^2	0.06	0.07	0.06	0.07	0.06	0.07

Note: 5201 observations. Coefficients on experience have been multiplied by 1000, experience squared by 10000, the Dixit-Stiglitz diversity index by 1000. Heteroskedasticity-consistent standard errors appear in parentheses.

Table 5A: Between-Job Wage Growth

Variable	*I*	*II*	*I*	*II*	*I*	*II*
College	0.66	-0.1	0.61	-0.13	0.61	-0.14
	(0.83)	(1.03)	(0.82)	(1.03)	(0.83)	(1.03)
Some College	1.93*	1.84*	1.95*	1.86*	1.93*	1.85*
	(0.85)	(0.91)	(0.84)	(0.91)	(0.84)	(0.91)
High School	0.76	0.73	0.75	0.73	0.76	0.74
	(0.62)	(0.64)	(0.61)	(0.63)	(0.62)	(0.64)
Experience	2.2	1.3	2.3	1.4	2.1	1.2
	(4.5)	(4.5)	(4.5)	(4.5)	(4.5)	(4.5)
Experience	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05
Squared	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Married	-0.14	-0.65	-0.1	-0.62	-0.14	-0.65
	(0.54)	(0.56)	(0.54)	(0.56)	(0.54)	(0.56)
Non-White	-0.57	-0.41	-0.58	-0.41	-0.56	-0.39
	(0.52)	(0.53)	(0.54)	(0.53)	(0.52)	(0.53)
Log Population	0.24*	0.22*	–	–	–	–
	(0.13)	(0.13)				
Log Density	–	–	0.32*	0.28*	–	–
			(0.14)	(0.15)		
Diversity	–	–	–	–	5.3*	4.9*
					(2.5)	(2.5)
Industry Indicators	No	Yes	No	Yes	No	Yes
Occupation Indicators	No	Yes	No	Yes	No	Yes
R^2	0.002	0.02	0.003	0.02	0.003	0.02

Note: 3923 observations. Coefficients on experience have been multiplied by 1000, experience squared by 10000, the Dixit-Stiglitz diversity index by 1000. An asterisk (*) denotes significance at 10 percent confidence or better. Heteroskedasticity-consistent standard errors appear in parentheses.

Table 5B: Between-Job Wage Changes

Variable	*I*	*II*	*I*	*II*	*I*	*II*
College	0.024	0.001	0.021	-0.0003	0.022	-0.000001
	(0.021)	(0.03)	(0.021)	(0.03)	(0.021)	(0.03)
Some College	0.033	0.034	0.033	0.035	0.033	0.034
	(0.021)	(0.023)	(0.021)	(0.023)	(0.021)	(0.023)
High School	0.011	0.013	0.012	0.013	0.011	0.013
	(0.018)	(0.018)	(0.017)	(0.018)	(0.018)	(0.018)
Experience	-0.27*	-0.32*	-0.27*	-0.32*	-0.27*	-0.32*
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
Experience Squared	0.001	0.001	0.001	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Married	0.015	-0.003	0.017	-0.001	0.015	-0.003
	(0.015)	(0.015)	(0.015)	(0.01)	(0.015)	(0.015)
Non-White	-0.036*	-0.03*	-0.037*	-0.029*	-0.036*	-0.028*
	(0.013)	(0.014)	(0.013)	(0.014)	(0.013)	(0.014)
Log Population	0.006*	0.006	–	–	–	–
	(0.003)	(0.004)				
Log Density	–	–	0.009*	0.009*	–	–
			(0.004)	(0.004)		
Diversity	–	–	–	–	0.13*	0.14*
					(0.06)	(0.07)
Industry Indicators	No	Yes	No	Yes	No	Yes
Occupation Indicators	No	Yes	No	Yes	No	Yes
R^2	0.007	0.03	0.007	0.03	0.007	0.03

Note: 3923 observations. Coefficients on experience have been multiplied by 1000, experience squared by 10000, the Dixit-Stiglitz diversity index by 1000. An asterisk (*) denotes significance at 10 percent confidence or better. Heteroskedasticity-consistent standard errors appear in parentheses.

Table 6: Robustness

Dependent Variable	Modification	Log Population	Log Density	Diversity
Within-Job Wage Growth	Episode Indicators	0.016 (0.024)	0.023 (0.026)	0.28 (0.43)
	Non-Movers Only	0.004 (0.006)	0.007 (0.006)	0.03 (0.1)
Within-Job Wage Changes	Episode Indicators	-0.0001 (0.003)	-0.0006 (0.003)	-0.016 (0.05)
	Non-Movers Only	-0.002 (0.004)	-0.001 (0.004)	-0.048 (0.076)
Between-Job Wage Growth	Episode Indicators	0.22* (0.13)	0.28* (0.14)	4.9* (2.5)
	Industry Change Indicator	0.22* (0.13)	0.28* (0.15)	4.8* (2.5)
	Geographic Move Indicators	0.23* (0.14)	0.29* (0.14)	5.2* (2.6)
	Non-Movers Only	0.29* (0.18)	0.22 (0.17)	4.4 (3.5)
Between-Job Wage Changes	Episode Indicators	0.006 (0.004)	0.009* (0.004)	0.14* (0.07)
	Industry Change Indicator	0.006 (0.004)	0.009* (0.004)	0.14* (0.07)
	Geographic Move Indicators	0.006 (0.004)	0.01* (0.004)	0.14* (0.07)
	Non-Movers Only	0.007 (0.005)	0.01* (0.005)	0.11 (0.1)

Note: 5201 within-job observations (2930 for non-movers); 3923 between-job observations (2072 for non-movers). Coefficients on log population, log density, and diversity from specification *II* of Tables 4-5. An asterisk (*) denotes significance at 10 percent confidence or better. Heteroskedasticity-consistent standard errors appear in parentheses.

A Appendix

A.1 National Longitudinal Survey of Youth 1979 Data

Data on individual work histories are derived from the geocoded files of the National Longitudinal Survey of Youth 1979 (NLSY79). As noted in the text, the sample of jobs is limited to full-time positions (i.e. involving at least 30 hours per week), for which industry and occupation codes are identified, and which are held after all schooling is completed. Because these post-education jobs must be numbered (i.e. first job, second job, third job), I only include those workers who report having initially been in school at the 1979 interview (i.e. their work histories beginning in January of 1978 initially code them as being in school). This procedure helps ensure that the job numbers I assign to each worker's job history are reasonably accurate.

The sample is restricted to individuals for whom an interview is conducted each year (1979-1994) to help ensure a correct coding of geographic location and other covariates which are only observed on interview dates (e.g. marital status). Workers who have missing values for their places-of-residence in any year are dropped unless all of the identified locations are the same. In these cases, I assume that the missing locations are the same as the identified locations. Places-of-residence are identified by the information provided at each interview and then mapped forward in time (as is marital status). That is, the county-of-residence reported in 1990, for example, is assumed to be a worker's county of residence between the 1990 interview week and the 1991 interview week when it may change. Changes to a worker's place-of-residence (or marital status) from one year to the next, therefore, are assumed to begin on the new interview date. There is, however, one important exception to this procedure. In the event that a worker reports a new place-of-residence, but the job held in that new residence is reported to have started at some date prior to the interview, I assume the worker's place-of-residence changed at the beginning of that job. Marital status and place-of-residence in the year 1978 are assumed to be the same as what is reported at the 1979 interview.

Confining the sample to workers who are identified in every year also facilitates matching job codes across years. Because the same job may be reported with a different job code in different years (e.g. the second job held in the year 1990 may be the same as the first job held in 1991), the NLSY79 provides a correspondence between jobs reported in the current interview year and whether these jobs were reported in the previous interview year. This information allows me to create a consistent set of job codes across years thereby eliminating the likelihood of treating a change in a job code within the same job as a job change.

Workers sometimes report changes in industry or occupation while on the same job. To ensure that each job falls into a single industrial and occupational grouping, I follow Neal (1999) and edit the codes where within-job industry and occupation changes have been reported. In particular, I assume that a job's industry and occupation are given by the codes the worker first reports for it.

Once I have constructed a complete weekly array of jobs, I identify job changes as points where the job codes change. Hence, if a job involves a worker moving in and out of employment, say due to temporary layoffs, no job change is recorded over this period. A job change requires the movement into another position. With job changes identified, jobs are numbered based on their position in the sequence. Cumulative work experience is calculated as a running total of all weeks in which a worker reports having a full-time job.

Reported wages for jobs sometimes take on implausibly low or high values in the NLSY79. To eliminate the influence of outlier observations, I restrict the set of jobs to those in which the initial and final wages lie between \$ 1 and \$ 250 per hour (in year 2000 \$). Nominal wages are converted to real terms using the Personal Consumption Expenditures Chain-Type Price Index of the National Income and Product Accounts. The mean hourly wage over the resulting 5201 observed jobs in the final sample is \$ 11.71 (minimum = \$1.07, maximum = \$ 160.87).

A.2 Additional Data Details

Local market population density is calculated as a weighted average of county-level densities across all counties belonging to the market. A county's weight in the calculation is given by its share of total local market population. This particular density measure helps to mitigate somewhat the problems generated by metropolitan areas containing extremely large, but relatively unpopulated, counties such as some of those in the western United States.

The industry coverage in the County Business Patterns files is reasonably complete. Excluded are workers in railroads, agricultural production, and most government. Due to disclosure restrictions, County Business Patterns does not always identify employment figures at the county level for all industries, especially those at the four-digit (SIC) level. Where the data are suppressed, one of the following employment ranges is given: 0 to 19, 20 to 99, 100 to 249, 250 to 499, 500 to 999, 1000 to 2499, 2500 to 4999, 5000 to 9999, 10000 to 24999, 25000 to 49999, 50000 to 99999, 100000 or more. The largest of these intervals did not appear in any of the data used here. To construct the Dixit-Stiglitz diversity index, I impute all undisclosed employment figures as the midpoint of the reported range. Total local market employment is estimated as the sum over industry-level employments so that, within each market, industry shares sum to 1.

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